Specialize? Or diversify? Or do Both?

- Niche Width Strategies in Emerging, Technology Based Industries

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INTRODUCTION

The success of technology based firms hinges greatly upon their strategic fitness within two key domains: output markets (Carroll, 1985) and technology (Podolny, Stuart, & Hannan, 1996). First and foremost, the better firms are able to develop and deliver valuable outputs to customers within a focal target market, the better chances of success they have. Market based success is a function of an optimal market focus and position as well as the demand potential underlying the targeted market. However, the value-added that that technology based firms ultimately deliver to their customers is based on an extensive and complex platform of technological knowledge and routines. Technology thus represents the inputs to a firm's productive process, whereby routines are required to turn the technological-scientific knowledge into tradable outputs that are perceived valuable by the customers. Despite normal mechanisms of market-based competition, much of competitive racing actually take place in the technological domain (Barnett & McKendrick, 2004; Barnett & Pontikes, 2008).

The strategic management of technology based firms is thus largely centered on choices regarding market scope (market position and focus) and technological scope (the technology the company needs to master and control in order for sustained value creation for the customers). For the market dimension, central strategic questions include: Which output markets and related demand should we focus on? How are market demand and preferences distributed and where can we best add value? What is the optimal market position and optimal market coverage? Should we aim at several different areas of application (and thus customer segments) or focus on just one? For the technological dimension, central strategic questions include: What kind of a technological competence base do we need to have now and in the future? Which technology is core and what are the required surrounding technologies or technological platforms? How is the core technology related to the surrounding technology? What should be developed in-house and which knowledge can be acquired from external network structures? Which technology needs to be kept under strategic control through patents and other methods of IPR protection? In general, how broad should a firm's internal technology portfolio be? I.e. what would be the firm's optimal strategic scope from a technological point of view?

Researchers in organizational ecology (Hannan & Freeman, 1977) and strategic management (Porter, 1985) have proposed two broad categories of strategic scope, generalist strategy (broad focus) and specialist strategy (narrow focus). Specialist firms focus on a narrowly defined market segment and/or a slim set of technological competence. Specialists gain competitive advantage through optimizing their processes to produce a specific output as efficiently as possible, with minimum changes and adjustments to the production system. Thus specialists fit best to stable or fairly predictable environments, or situations where the environment changes relatively frequently between a finite number of states (e.g. seasonal demand fluctuation) (Freeman & Hannan, 1983; Hannan et al., 1977). In contrast, generalists hold a broader market focus and a more central market position. In the technological domain, generalists develop and maintain broad sets of technological knowledge and routines. Due to their broad scope, generalists have considerable "slack" or "buffer" that becomes useful when unpredictable, coarse-grained changes take place in the environment. However, the very same breadth of activities and related excess capacity acts as competitive disadvantage to generalists over specialists in terms of productive efficiency (Freeman et al., 1983; Hannan et al., 1977).

A considerable body of ecological research has argued and demonstrated that – despite their relative advantages/disadvantages in different conditions of environmental change – generalism and specialism are in fact interrelated and mutualistic realizations of an organizational form that do often co-exist. In particular, the resource partitioning theory (Carroll, 1985) holds that the crowding of generalist firms in market centers frees up resources for specialist organizations in peripheral areas. Resource partitioning theory has been successfully applied to explain the resurgence of organizational densities in mature industries such as brewing (Carroll & Swaminathan, 2000b), automobiles (Dobrev, Kim, & Hannan, 2001), and daily newspapers (Boone, Carroll, & van Witteloostuijn, 2004). However, the explicit focus on (very) mature industries relates to a number of core assumptions behind the theory. First, it is assumed that the carrying capacity of the underlying niche has been reached and possibly exceeded long ago. Thus a strong level of ecological competition has imposed selective pressures on organizations for an extended period of time. Second, because of the above, processes of consolidation and crowding have taken place at the market center.

It becomes apparent that existing research has not thoroughly investigated and problematized how the dynamics of generalist vs. specialist strategies unfold in emerging, technology based industries where the environmental carrying capacity has not yet been exhausted and/or is expanding rapidly (cf. Dobrev, 2000). Such settings are characterized, it is argued, by strong levels of uncertainty and coarse-grained variation in the technological domain and often more stable and predictable market conditions – at least relative to the technological domain. The emergent nature of such industries means that the existing population of organizations does not consume all available resources from the environment (market demand in particular) and thus the related carrying capacity is not reached. In addition, the resource endowments may even be constantly increasing, as exemplified by the demand for healthcare and wellness related products and services. Such relationships between organizations and environmental resources represent completely different circumstances for competitive interaction and firm strategies compared to crowded mature industries.

The present paper contributes to strategy and ecology research (cf. Dobrev, van Witteloostuijn, & Baum, 2006), by conceptually elaborating and empirically examining what drives the relative advantage or disadvantage of generalist vs. specialist strategies in emerging populations of technology based firms. The specific research questions are: *How does the choice between generalist vs. specialist strategy affect firm survival in emerging, technology based industries that operate below carrying capacity? How does the effect of the choice between generalist vs. specialist strategy differ between the two dimensions of market and technology?*

It is proposed that due to unpredictability, “red queen” competitive races (Barnett & Hansen, 1996), and other characteristics associated to the technological dimension and related environmental change, firms that hold a broad technological scope (i.e. generalists) have better chances of survival. At the same time, firms holding a narrow market scope (i.e. specialists) will survive better because of disadvantages from multiple category membership (Hsu, 2006), lack of positional advantages, and relative stability of the environment. The proposed effects are statistically modeled and tested with data from the modern biotechnology industry in Finland between 1973-2006.

The paper proceeds by first proposing a conceptual model to account for generalism and specialism separately within the technological and market domains. The characteristics of an emerging, technology based industry are also scrutinized. Based on the conceptual model and related assumptions, hypotheses regarding the effects of generalist vs. specialist scope on firm survival are derived. Based on the findings from the empirical analysis, implications to theory and method are discussed in length.

THEORETICAL BACKGROUND

Niche and Resources

Organizations are generally regarded to be strongly dependent upon a complex set of social and material resources from their external environments (Aldrich, 1979; Pfeffer & Salancik, 1978). The ecological approach holds that fitness to the resource endowments available in organizations' external environments ultimately determines organizational success and survival. On top of this, organizational environments are regarded as diverse, discontinuous and unstable (Hannan & Freeman, 1989, p. 13). The diversity and discontinuity results in special combinations of environmental resources and conditions called *niches* (Hannan et al., 1977). Specific organizational forms tend to develop around such niches, where organizations representing the form are able to take utilize the niche-specific resource combinations in an optimal way in comparison to any other form (Freeman et al., 1983). Thus a niche can be defined as the set of social, economic, and political resources and conditions from the environment that are required for organizations representing a particular form to persist (Hannan *et al.*, 1977).

Organizational forms are abstract organizational "blueprints" (Hannan et al., 1977) or "identities" (Polos, Hannan, & Carroll, 2002) that get realized as spatially and temporally bounded organizational populations, whose members share a common form, i.e. are similar in a fundamental way. However, it is important to note that organizational forms tend to be hierarchical, and different kinds of sub-forms (and thus sub-populations) may develop under a general form (Carroll & Hannan, 2000a; Mattsson, 2008; McKendrick & Carroll, 2001; Ruef, 2000). Even though the general environmental niche is the same for all sub-forms, specific sub-forms may occupy distinct positions (resource combinations) within the niche, such as specialist vs. generalist organizations.

In the context of technology based industries, two central dimensions stand out in the underlying resource niche that have a profound effect on firm survival: (i) markets for the firm's outputs and (ii) technological knowledge and routines. As noted earlier, demand for a firm's outputs is a central underlying resource dimension within the firm's immediate resource environment/niche (Carroll, 1985). Thus the customer focus and related market demand targeted by a technology based firm determines the scope of the firm's activities and sets the ultimate selection environment for the outputs of the firm. The market domain is generally regarded as the key dimension by which the *carrying capacity* of a niche is measured. Carrying capacity relates to the finite availability of key resources from the environment and is defined as the maximum number of organizations a niche can simultaneously sustain (McPherson, 1983).

In additions to market demand, another central dimension of the environmental resource space is defined by technology (Podolny et al., 1996). This relates not only to technological-scientific knowledge but also routines and processes that firms use in turning the knowledge into deliverable, value-adding products and services to their customers and other stakeholders (Tushman & Anderson, 1986). The centrality of the technology dimension is apparent through the definition of many related industries and firm populations. For example, biotechnology represents an industry whose boundaries are defined by the underpinning core technology (cf. Calabrese, Baum, & Silverman, 2000). In other words, the biotechnology industry consists of those organizations whose core activities are related to a set of (bio)technologies. Central industry organizations such OECD or the Biotecnology Industry Organization BIO even provide lists of defining technologies for biotechnology.

However, even though the existence of markets (i.e. demand for firm outputs) is critical to the success of any for profit organization, in technology based industries, the highest intensity of ecological competition resides largely in the technological domain (Barnett et al., 2004; Barnett et al., 2008). Firms that most systematically generate and capture technological innovation in relation to the surrounding technological space have good chances of dominating ecological competition. As an illustrative example, consider biotechnology firms producing pharmaceutical products. Naturally the key enabling resource dimension for such organizational activity is the existence of different types of diseases and other medical conditions requiring corrective action. However, the related worldwide demand for pharmaceutical products is more or less given and accessible to any firm entering the field. However, the basis for "red queen" type ecological competition relates to the technological dimension. Firms compete for being the first one to develop, commercialize and protect a viable pharmaceutical product for the curing of a given disease. This requires substantial investments in technological knowledge and routines through complex and prolonged R&D processes. Whoever first comes up with a potential solution may protect the invention through a patent, thus precluding others from proceeding in identical lines of development – thus controlling part of the resource space and thus increasing diffuse competitive pressures in the field.

Other important dimensions of the environmental niche underlying technology based industries include (i) social capital and collaborative network relationships, (ii) financial resources, and (iii) the institutional environment. First, technological knowledge and related productive routines do not always reside inside the boundaries of a firm. In contrast, technology based firms increasingly adopt strategies and structures to access technological knowledge and perform related routines outside the boundaries of the firm (Powell, Koput, & Smith-Doerr, 1996a; Walker, Kogut, & Shan, 1997). In the biotechnology case, firms tend to have deeply rooted organizational and individual level network relationships to university research to maintain and constantly update their technological knowledge base (Oliver, 2004; Owen-Smith & Powell, 2004). Such network structures give the firm a vital access to additional knowledge that the firm does not possess, but is potentially required by the firm's technological development activities. Similarly, biopharmaceuticals often outsource non-core development activities, such as clinical trials, to external technology partners. Even though important as a resource dimension, the role of the social/network dimension in the resource space is more or less derived from the technological dimension (Baum, Calabrese, & Silverman, 2000; Calabrese et al., 2000; Oliver, 2001a; Powell, White, Koput, & Owen-Smith, 2005). Thus strategic choices regarding the social/network dimension ultimately boil down to decisions concerning the technological scope.

Second, financial resources are critical enablers of sustained R&D to develop and maintain technological knowledge and control, and to carry out related productive activities (Lerner, Shane, & Tsai, 2003). The owners of a firm impose restrictions on strategic scope and resource utilization through controlling the financial resources of the firm. The market mechanism to obtain funding from investors acts also as a selection environment against the strategic direction and scope of firms – both in the output and technology dimensions.

Finally, besides the resource space that sets bounds to a niche, also different constraining factors control the underlying organizational form and the activities performed by related organizations. In the context of technology based industries, the regulative-institutional dimension sets up an important selection and constraint environment for the inputs, outputs and operational forms of technology firms (McKelvey, 1996). In the example of biopharmaceutical firms, this can be illustrated at several instances. The regulative and approval processes by the U.S. based Foof and Drug Administration FDA in and other regulating bodies ultimately determine whether a pharmaceutical product can be brought to the market. Similar regulative and standardization processes are in place to control the R&D and production activities of such firms. Several institutional processes affect the legitimation and viability of the biotechnology form, including the institutional pressures stemming from ethical issues related to e.g. genetic engineering. To add, the patent system acts in its own way to institutionalize control over technological domains for long periods of time. Finally, biotechnology firms are dependent upon different political-legal processes that set the ultimate limits to their behavior.

Generalism and Specialism in Technology-Based Industries

Regarding the research questions being addressed by the present paper, it is important to make a distinction between generalism and specialism in the market and technology dimensions (cf. Sorenson, McEvily, Ren, & Roy, 2006). In the market domain, the level of generalism/specialism is a function of both market coverage and position (cf. Carroll, 1985; Freeman et al., 1983; Hannan et al., 1977). Market coverage refers to the breadth of a firm's outputs: what is the diversity of the market offering and thus the scope of market demand addressed. Firms with broad coverage may simultaneously offer diversified products, services and solutions, and even target to different sectors. In contrast, narrow coverage implies a strict focus on a specific market segment. Market position, on the other hand, refers to the location of the firm's offering within a given market space. In particular, firms may adopt positions close to market centers (mainstream) or periphery ("niche markets"). Typically market size/potential is highest at the market centre and decreases towards the periphery. From the biopharmaceutical domain, an illustrative example of market position is the distinction between drugs targeted to mainstream syndromes (e.g. painkillers or common antibiotics) versus specialty drugs (e.g. specialty cancer treatment). The above dimensions of the market space are visualized in Figure 1. In this depiction, a firm's market scope (i.e. level of generalism/specialism) can be inferred from the shaded areas, i.e. the product of market coverage and the market size associated with the market position.

Figure 1 about here

As for the technological domain, generalism vs. specialism is essentially defined by the breadth of technological knowledge and routines that are being directly utilized by the firm's R&D or (other) production processes, situated either inside the firm, or being accessed through the firm's existing network connections. In addition, firms may hold a stock of additional knowhow and routines that is not currently utilized, but whose utilization, if needed, would be possible in a relatively immediate and straightforward way. A firm's technological scope thus depends on the amount and diversity of available technological knowledge and routines (cf. Podolny et al., 1996).

It is important to note that a firm's scope in the market and technology dimensions are two distinct choices, i.e. specialism in one does not imply specialism in the other. It is possible that a firm holds a central market position and thus generalist strategy in the market domain, but utilizes a relatively narrow/optimized set of technology to produce the related outputs. Likewise, other firms may be building a broad technological base while targeting a narrow specialist market. Figure 2 provides a graphical summary of the different dimensions and thus brings additional clarification to the concepts of generalist and specialist strategy in the technology based context.

Figure 2 about here

Based on the above conceptualization (as illustrated by Figure 2), four general options can be identified for a firm’s strategic scope in technology based industries. First, firms can adopt a specialist strategy or a generalist strategy on both dimensions (top-left and bottom-right corners, respectively). This corresponds to classic doctrine in strategic management regarding focus vs. diversification strategies. However, two additional scope options are available. The bottom-left corner in Figure 2 represents a strategy of developing a broad technological base but focusing on a narrowly defined target market. Similarly, the top-right corner represents firms that hold a generalist scope in the market dimension but operate on a relatively narrow technological base.

Form Evolution

An implicit mainstream assumption among strategic management scholars and practitioners holds that as organizations mature and grow, they follow a more or less straight line path from specialism to generalism on both dimensions. The underlying explanation is simple and rather general: as organizations age, they reinvest returns to growth. Predominant ways for growth include broadening the market scope as well as building additional knowledge and routines. However, when the level of analysis is extended to the evolution of the underlying organizational form, different paths seem plausible (cf. Dobrev, Kim, & Carroll, 2002).

Based on assumptions elaborated in the next section, it is proposed that in the emergence and growth phases of a technology based industry, the predominant scope of the underlying organizational form moves from pure specialism towards pure generalism (i.e. same scope on both dimensions). However, the path takes through the bottom-left corner as depicted in Figure 2. In other words, the very first entrants to the population are specialists on both dimensions. As the field develops and new organizations enter, the entrants' focus shifts towards generalism in the technological domain (cf. Sorensen & Stuart, 2000). As the industry life-cycle approaches maturity (i.e. carrying capacity is approached), the predominant strategy among the members shifts towards generalism. However, as the resource partitioning mechanism suggests, consolidation and crowding eventually takes place at the market center. This leads to the re-opening of resource spaces (micro-niches) at the market periphery. Eventually generalist and specialist forms begin to co-exist as new specialist organizations enter and market-generalists get distributed between technological specialism and generalism (cf. Carroll et al., 2000b). Figure 3 below summarizes the evolutionary paths outlined above.

Figure 3 about here

HYPOTHESES

Technological Scope

It is proposed that it is beneficial for firms operating in emerging, technology based industries to hold a generalist strategy within the technological dimension. Several explanations support the argument. First, it has been suggested that the nature of environmental change generally affects the viability of either generalist or specialist strategy over the other (Hannan et al., 1977). According to the original argument, generalist strategy has advantage over specialism only in situations where environmental change is both unpredictable and what Hannan and Freeman (1977) call "coarse-grained".

It is evident that environmental change and variation in the technological domain is both unpredictable and coarse-grained. The former arises from the risky nature of technological development (Podolny & Stuart, 1995). There is always limited a priori knowledge of which technological innovations, solutions and development streams will eventually work out and develop into commercial applications and even dominant designs (Anderson & Tushman, 1990). In other words, technological variation is blind and relatively strict selection mechanisms eventually determine the success of individual technologies. Thus it is beneficial for firms to develop a broad base of technological knowledge and routines to (a) maximize the likelihood of coming up with a successful technology, and to (b) limit firm level risks from possible technological failure (thus existing coordination/support routines can be utilized in developing other technologies).

Technological change is also coarse-grained, i.e. disruptive changes take place relatively infrequently, and the environmental states after such changes are not known a priori. Several mechanisms produce such kind of coarse-grained change. Technology based R&D cycles tend to be quite long and thus new innovations develop relatively infrequently. However, part of such innovations tends to be radical and “frame-breaking” in nature (Tushman et al., 1986). In addition, many technology based industries have a strong dependence relationship to regulatory and standardization bodies. The processes of standardization and regulatory change are relatively slow but may eventually generate major institutional change affecting whole industries and economies. Furthermore, the patenting system still emphasizes the coarse-grained nature of technological development. Patents act as one-off events that institutionalize technological control over extended periods of time. Following Hannan and Freeman’s (1977) original argument, also the coarse-grained nature of technological change promotes technological generalism. To protect from unpredictable, sudden, and radical changes in the technological domain – be it innovations, regulatory change, or patent protection – firms gain advantage from holding broad technological bases to support their market activities.

Besides the nature of technological change, emerging populations tend to consume less resources (market demand in particular) from the environment than the carrying capacity would allow. The number of firms is likely to be simply lower than the carrying capacity of the local niche would allow. In addition to this, many technology based industries tend to have worldwide markets. This means that market demand gets spilled over from worldwide niches to a local niche, thus rendering the actual carrying capacity much higher than simply the local demand for products and services. Finally, for some emerging industries the carrying capacity may be constantly broadening, as exemplified by the demand for healthcare and wellness related products and services.

Because the frontier of carrying capacity and thus the distribution of yet untapped markets is largely unknown, it is beneficial for firms to develop a broad base of technological knowledge and routines to be able to quickly capture new, markets areas being discovered or opened up. In addition, because the carrying capacity is not yet reached and simultaneously broadening, firms tend to enter into intensive ”red queen” type competitive races for technological control and dominance. The patent system is an enabling institutional framework for such technology races. Thus it is beneficial for firms to develop a broad base of technological knowledge and routines to build/ensure relative technological readiness and dominance/control in the future.

Finally, Pursuing generalism in the technological domain requires relatively high capital investments. This means that firm ownership control and acts of capital investment take place by professional level actors and processes. This usually leads to early professionalization of firm management which again has a positive effect on firm survival.

Given the above, specialist strategy in the technological domain would be particularly vulnerable: There is a high risk that well developed technologies fail. In biopharmaceuticals, a promising mechanism to cure a disease might quickly turn to a failure if clinical trials eventually show unacceptable results (e.g. toxicity). Without complementing tracks of R&D, such a situation would mean immediate death to a firm. In addition, sticking to a narrow technological range for long periods of time holds additional risk of failure because of constantly changing environment. Finally, narrower technological scope means less control over the value generated by the overall system. Technological specialist firms have less ability to capture parts of the related revenue streams, and thus face lower survival chances.

Based on the above, we hypothesize:

H1: In emerging, technology based industries that operate below carrying capacity, generalism in the technological domain has a positive effect on firm survival.

Market Scope

Contrasting with the technological domain, it is proposed that it is beneficial for firms operating in emerging, technology based industries to hold a specialist strategy within the market dimension. Consider first environmental change. It is argued that, relative to the technological domain, environmental change in the market domain is more predictable and also fine-grained. Even though new market categories and related demand for products and services tend to emerge every now and then (e.g. MP3 players), this dimension is often much more predictable than technological change. Changes in the market domain relate ultimately to changes in consumer taste and preferences. This again follows general demographic change, which is fairly predictable and fine-grained in nature. For example, the distribution and intensity of different syndromes and therapeutic areas tend to be relatively stable and known. Thus the demand for medical cure is relatively stable compared to the space of possible technological solutions. Because of the nature of environmental change in the market domain, firms are able to concentrate their efforts and thus gain productive efficiency by focusing on specific target markets and related customer solutions/offerings. Even though considerable ”buffer” brings advantage in the technological domain (due to risk/uncertainty) this is not the case regarding the market dimension.

Second, because emerging industries operate well below carrying capacity, the level of generalism vs. specialism essentially reduces to market coverage. In other words, firms cannot enjoy from substantial positional advantages in such circumstances. Positioning in the market centre, for instance, doesn’t involve a big difference for a local player facing a worldwide market potential. In contrast, a local specialist/peripheral player may hold an equal attainable market potential and thus comparable chances of success. Because the sheer size difference between total demand and the productive capacity of individual firms, positional differences between market center vs. periphery become insignificant. The above logic is illustrated by Figure 4 below.

Figure 4 about here

Finally, research has demonstrated that organizations’ membership in multiple (market) categories has a negative effect on success when compared to narrower market focus. An increasing body has examined mechanisms by which different external audiences hold collective understandings or identities regarding organizational forms/categories (Hannan, 2005; Hsu & Hannan, 2005; Polos et al., 2002). Such audiences constantly screen individual organizations' properties and behavior and evaluate their conformity to sets of rule-like codes that the audiences associate with specific forms. Organizations' disconformity to such expected codes affects negatively audiences' valuations of the organizations, and thus ultimately the organizations viability. It is argued that targeting multiple audiences forces organizations to adopt properties and behavior that partially misfits the identity codes held by an individual audience. As the number of audiences/categories increases, the average fit to any audience's code-set decreases, thus affecting negatively overall valuations and firm survival (Hsu, 2006; Hsu, Hannan, & Kocak, 2007). An example of this would be a biotechnology firm operating simultaneously on pharmaceutical, diagnostics and biomaterials sectors. Such a firm would find it difficult to build a unified reputation within the targeted sectors, and need to hold complex product ranges, production systems, and sales & distribution processes.

Combining the above lines of reasoning, we hypothesize:

H2: In emerging, technology based industries that operate below carrying capacity, generalism in the market domain has a negative effect on firm survival.

METHODOLOGY

Data

We test our hypotheses with data covering life-histories of all dedicated biotechnology firms ever operated in the Finnish modern biotechnology industry. The data is obtained from the GloStra biotechnology database, developed and maintained by Helsinki University of

Technology. The database comprises information of all firms[1] that have ever operated in the Finnish biotechnology industry.

As regards the identification process of the firms in the database, several sources have been triangulated. First, different biotechnology listings were used as a starting point. The *Index of Biotechnology Companies, Organizations and Research Institutes in Finland* published annually by the Finnish Bioindustries association (FIB) in 1997-2006 proved to be clearly the most comprehensive source. Additionally, several international biotechnology firm listings were also investigated, such as the Bioscan Directory (published by Thomson BioWorld), several volumes of the International Biotechnology Directory by Coombs (Coombs, 1984, 1986), as well as the Genetic Engineering and Biotechnology Firms Worldwide Directory of 1983/1984 and 1985 (published by Sitting & Noyes). However, all these international sources covered the Finnish industry extremely shallowly.

Second, a comprehensive news-event database was created in order to patch the problems of historically incomplete information and lack of coverage of the industry directories and indices. All Finnish biotechnology related articles and news were coded to the database from the following sources: *Kemia-Kemi* (1974-2005), *Kauppalehti* (1974-2005), *Insinööriuutiset* (1974-1989), and *Tekniikka & Talous* (1990-2005). *Kemia-Kemi* is the leading Finnish (bio)chemistry oriented, semi-academic industry journal. The journal has constantly featured related articles and entire special issues in biotechnology, including topics

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[1] Both dedicated biotechnology firms (DBFs) and firms with only some biotechnology activities (e.g., incumbent pharmaceutical and chemical industry firms operating in the industry). The definition of biotechnology by OECD (2004) was used as a guideline in the firm identification process. The reliability of the data was checked by a special card-sorting technique in interviews with six industry experts.

ranging from industry news to market trends to technological developments. Most of the articles mention one or more companies. *Kauppalehti*, on the other hand, is the leading daily trade newspaper in Finland. Finally, *Insinööriuutiset* and its successor, *Tekniikka & Talous*, are technology-oriented Finnish newspapers published weekly. In total, the database contains over 3000 news events; for instance, all the news events related to collaborative activities, financing, and new product launches have been coded. Third, all biotechnology patents granted in Finland between 1970-2006 were screened (Source: the Esp@cenet database maintained by the Finnish patent authorities. The definition of biotechnology patent classes by the OECD was applied (OECD, 2004).

After identifying the firm population, the basic characteristics (i.e., entry and exit dates) of the included firms were coded based on data offered by the National Board of Patents and Registration of Finland (NBPR). NBPR maintains a record of all corporations and other legal entities operating in Finland. NBPR registration is required by law. Thus, NBPR holds a record of every firm that operates or has operated in Finland, including basic data such as founding and disbanding dates, as well as mergers with other entities.

To construct the data-set for this paper, we queried the GloStra biotechnology database for all Finnish dedicated biotechnology firms founded after 1973, which is commonly considered as the year of birth of the modern biotechnology industry (see e.g., Powell et al., 1996a; Prevezer, 1997, 1998, 2001; Stuart, Hoang, & Hybels, 1999). However, the first Finnish dedicated biotechnology firm was founded just in 1978. In total, we identified 163 biotechnology firms that operated in one or more of the 12 following biotechnology sectors: (1) biopharmaceuticals, (2) human diagnostics, (3) agrobiotech, (4) bioinformatics, (5) biomaterials, (6) bioproduction, (7) industrial enzymes, (8) the environment, (9) functional food, (10) bioenergy, (11) devices and equipments, and (12) R&D services. As the industry is populated by a diverse set of organizations that operate in various product markets with different strategies and business models (Baum et al., 2000), and consequently, is rather heterogenic, in testing our Hypothesis 1 (technological domain), we focus only on firms operating in the following healthcare biotechnology sectors (Mattsson, 2008; Powell et al., 1996a; see also Shan, Walker, & Kogut, 1994; Stuart et al., 1999): biopharmaceuticals, human diagnostics, and biomaterials. In addition to the fact that firms in these sectors usually operate under similar business models and strategies and compete in similar types of markets (healthcare biotechnology), building strong patent portfolios is important to them. Thus, considering that we are particularly interested in technological generalism and specialism of the biotechnology firms, and operationalize our technological niche width constructs by employing patent data, firms operating in these sectors are ideal for our analyses. In contrast, in testing Hypothesis 2 (market domain) we employ data of the all dedicated biotechnology firms.

Consequently, the research sample for testing Hypotehsis 1 consisted of 87 healthcare biotechnology firms (53.4 % of all biotechnology firms; denoted as “sample 1” from this point forward), and the sample for testing Hypothesis 2 of 163 dedicated biotechnology firms (“sample 2”). For each of these firms, we generated yearly updated life-histories for the time period of 1978-2006. Thus, for a firm established in 1978, and still in operation in the end of 2006, we generated 29 observations in total. In the following, we describe the operationalization of our constructs and describe the additional databases we used in collecting the empirical data for the constructs.

Dependent Variable

The dependent variable in our study is the rate of exit (failure) of biotechnology firms. We define exit as the failure of a firm or closure of a subsidiary. As is the norm in organizational failure studies (Baum, 1996), name changes and acquisitions are not considered failures because the firms continue to operate. In the two research samples, a firm fails if it goes bankrupt or if its value-added tax liability expires; without this, it is impossible to operate in Finland. We also detect 16 acquisitions and mergers that led to discontinuance of a firm. As acquisitions and mergers like these may not always imply failure, we treat these cases as right-censored, as is the convention in earlier research (Baum & Mezias, 1992).

Consequently, of the 87 firms in the sample 1, 34 exited the industry during the analysis period. 29 of the exits were failures, 2 were acquisitions, and 3 were mergers. Considering the sample 2, consisting of 163 firms, 69 firms exited the industry; 53 of these exits were failures, 10 were acquisitions, and 6 were mergers.

Independent Variables

To test Hypothesis 1 (the effect of technological niche width/scope on firm failure rate), we decided to use two operationalizations for the construct of niche width. Both of the variables build on patent data (cf., Podolny et al., 1996). Although patents are frequently used in measuring firms' inventions, innovativeness or technological positions, there are still some reasons to be cautious about the use of patents in measuring these issues. First, there might be differences in firms' propensity to patent their innovations, given the resource expenditure required by the patent process (DeCarolis & Deeds, 1999; Deeds, Decarolis, & Coombs, 1997). Second, firms might not patent certain innovations because they might fear that the public revelation of the innovation in the patent application will damage their competitive position more than will the lack of the patent application (Podolny et al., 1996). Third, industries vary in their propensities to patent (Levin, Klevorick, Nelson, & Winter, 1987).

Although especially the first problem might pose some problems to our study, given that many of the biotechnology firms we study are rather small-sized and may have resource restrictions as regards the patenting process, in general we see that patenting can be considered as an essential feature of the life of healthcare biotechnology firms: taking into consideration the long product development times of new human healthcare products and other industry characteristics (such as that the industry is highly science-based), healthcare biotechnology firms can be seen to compete in patent races against their rivals; running second in these races provides little if any benefit (Baum et al., 2000). In general, according to earlier research, particularly in human healthcare biotechnology, patents can be considered as indicators of important technology positions and innovation activity (e.g., Deeds et al., 1997). Particularly, patents are seen to help delay imitation by other firms and protect the firm's gains from R&D spending and product introductions (Zahra, 1996), and provide access to critical complementary assets: marketing-distribution infrastructure, production facilities, and expertise in managing clinical trials (Pisano, 1990). They also signal future potential of the firm (Baum & Silverman, 2004; Niosi, 2003).

As noted above, we measure firm's technological niche width in two ways. The first measure ($H1_{lt}$) is defined simply as a logarithm of the count of sub-classes in the patents in a firm's patent portfolio at the end of year *t*. Patent offices in most of the countries use sub-class references to indicate which technologies relate to the patent. The classification is based on International Patent Classification system developed by World Intellectual Property Organization and is frequently updated so that it enables to track technology back to 1970. The more than 70 000 sub-classes allow for fine-grained classification of inventions (Carr, 1995). Every patent belongs to at least on sub-class of technology and, as in our case, most patents (96 %) have multiple memberships.

Consequently, according to the measure, the more sub-class references a firm has in its patent portfolio, the more heterogeneous is its technological base. We treat the measure as cumulative and update its value yearly. Consequently, we do not set any predefined time window for defining a firm's current pool of technologies and innovations. As all of the firms in our sample are relatively young and as the product developments cycles in the industry are extremely long (e.g., product development process for a new drug can take more than 15 years) in comparison to many other technologically progressive industries (e.g., semiconductors (Podolny et al., 1996), we see this kind of procedure unnecessary. Furthermore, setting the value for the time-window is always somewhat arbitrary and may lead into erroneous results.

Our second measure builds on the patent level complexity measure introduced by Fleming & Sorenson (2001). The original measure is defined as an interaction of two components: (i) the degree of interdependence between components in a patent (i.e., the number of assigned sub-class references) (*K*) and (ii) the number of components in a patent (*N*). The interaction is calculated as a ratio of the terms (i.e., *N/K*).

The value for the interdependence K_l of patent l is calculated in two stages. First, equation (1) details the measurement of the ease of recombination (E_i), or inverse of interdependence, of an individual sub-class i used in patent l. It is calculated as the sum of the number of previous uses of the sub-class i in certain sample of patents divided by the count of number of different sub-classes appearing with sub-class i on previous patents. Thus, according to Fleming & Sorenson (2001), the value of the E increases as a particular sub-class combines with a wider variety of other sub-classes, controlling for the total number of applications. Consequently, the value of E captures the ease of combining a particular technology. Second, equation (2) details the measurement of the K_l for an entire patent l. It is defined as an inverse of the average of the ease of recombination scores for the sub-classes to which it belongs (Fleming et al., 2001).

$$E_i = \frac{\text{count of sub-classes previously combined with sub-class } i}{\text{count of previous patents in sub-class } i} \quad (1)$$

$$K_l = \frac{\text{count of sub-classes on patent } l}{\sum_{l \in i} E_i} \quad (2)$$

In the current paper, we apply the measure ($H2_{lt}$) at the firm level and calculate its value as a ratio between the number of sub-classes assigned to patents in the patent portfolio of firm l at the end of year t (N_l) and the inverse of the average of the ease of recombinance of the sub-classes in the patent portfolio of firm l at the end of year t (i.e., interdependence of the patent portfolio of firm l; K_l). We calculate the value for K_l according to equations 3 and 4.

$$E_i = \frac{\text{count of sub-classes combined with sub-class } i \text{ at the end of year } t \text{ (patent-portfolio level)}}{\text{count of firms with patent(s) in sub-class } i \text{ at the end of year } t} \quad (3)$$

$$K_l = \frac{\text{count of sub-classes in firm } l\text{'s patent portfolio at the end of year } t}{\sum_{l \in i} E_i} \quad (4)$$

Consequently, according to the measure, the technological niche width of a firm is a function of the number of sub-classes and interdependence of the firm’s patent portfolio; the more there are sub-classes in the patent portfolio and the lower its interdependence, the lower the value of the measure and the wider the firm’s technological niche. Following the earlier measure, we treat the measure as cumulative (thus, we do not set any time windows) and update its value yearly. In the regression models, we multiply the value of $H2_{lt}$ by 1000.

We used the espa@cenet patent database to identify all patents Finnish biotechnology firms had filed and been granted. Patents that were issued in many countries (often patents forming families) were only been coded once based on their first-found date of filing and granting. Following prior research, we assigned a patent to a firm at the date of application (filing) rather than the date of granting. This better takes into consideration the point of time the actual innovation was made. Although our observation period ended on December 31, 2006, we included information on patents granted up to August 31, 2008. We do this to limit truncation of the count of patents granted due to the time lag between the application and granting dates. In total, 68 of the firms in the sample 1 had filed or been issued a patent; the total number of patents the firms had filed until the end of the analysis period equaled 541. Additionally, we also identified firms that filed patents just few years after their founding. As we were not able to calculate heterogeneity measure values for either firms that had not filed any patents or for the yearly spells during which a firm had not yet filed patents, we excluded these spells from the regression models.

To test Hypothesis 2 (the effect of a firm's market niche width on its failure rate), we operationalized the construct of *market niche width* as the number of biotechnology sub-sectors in which a biotechnology firm is active at year *t*. The value of the variable is updated yearly. As was mentioned, we identified 12 biotechnology sectors in which the Finnish firms are active; many of the firms operate in more than one sub-sector. Thus, although the measure is rather crude (e.g., it does not take into account the proportion of activity of a firm at a certain sector), it still enables us to differentiate those firms that clearly focus their activity on only one sector from those that are active in multiple sub-fields.

Control variables

We also introduce several control variables into regression models in order to take into account various firm- and industry level characteristics that may affect biotechnology firms' failure rates. First, following earlier ecological research, we use *population density* measures to control for the processes of density dependent legitimation and competition. As the theory of the density dependence suggests, the relationship between density and mortality rates should have the shape of U (Hannan et al., 1989); thus we include both the linear and squared density variables into the models. However, because of the differences in the two research samples we use, we introduce somewhat different density variables depending on the sample. In case of Sample 1, we include two different level density measures: (i) healthcare firm population density (N_{he} and N_{he}^{2}) and (ii) the density of population of all Finnish biotechnology firms (N_{all} and N_{all}^{2}) (Mattsson, 2008). In case of Sample 2, we include the following density counts: (1) density of biotechnology firms active in sectors in which the focal firm is active (N_{sect} and $N_{sect}^{2}/100$) and (2) the density of population of all Finnish biotechnology firms (N_{all} and $N_{all}^{2}/1000$).

Second, in order to capture trends in the failure rate that are a function of historical time and population ageing, we introduce a *year* control variable. Its value is calculated by the year of the observation minus 1978. Third, to adjust for possible differences in failure rates between the different biotechnology sectors, we created dummy variables for the biotechnology sectors in which the firms in the sample operate. Consequently, as regards the sample 1, we introduced the following three dummy variables: (1) *biopharmaceuticals*, (2) *diagnostics*, and (3) *biomaterials*. Regarding Sample 2, we included 11 dummy variables for the identified sub-sectors (described earlier)[2]. Fourth, we introduced a control variable for *firm size*. The variable is operationalized as the number of firm's personnel. We derived the yearly data for the variable from Statistics Finland. Fifth, we controlled for a possibility that biotechnology firm's ownership status may affect its failure rate. Results of the earlier

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[2] We combine R&D –service and bioinformatics sectors together because firms active in these sectors are all service providers.

biotechnology research suggest that independent biotechnology firms experience better performance than subsidiaries (e.g., Zahra, 1996; Zahra & George, 1999). We operationalize *ownership status* as a yearly updated dummy variable coded “one” for independent biotechnology firms and “zero” for subsidiaries (we code three public firms in our sample to be in the same set with independent firms). The data for the yearly updated variable was obtained from by Statistics Finland.

Sixth, we control for a possibility that the number of biotechnology firms’ patents has a positive effect on firm performance and survival, as suggested by earlier biotechnology related research (DeCarolis et al., 1999; Deeds, Decarolis, & Coombs, 1998; Niosi, 2003; Silverman & Baum, 2002). Hence the *Patents* -variable is operationalized as the cumulative yearly updated number of patents a biotechnology firm has filed. Seventh, building on earlier biotechnology related research suggesting that the number of a biotechnology firm’s alliances has a positive effect on firm performance (Baum et al., 2000; Deeds & Hill, 1996; Gulati, 1998; Oliver, 2001b; Powell, Koput, & SmithDoerr, 1996b), we introduce the *alliances* -control variable. The variable is obtained by summing up the number of a firm’s vertical upstream (i.e., alliances with universities and research organizations), vertical downstream (i.e., alliances with pharmaceutical, chemical, or marketing firms), and horizontal alliances (i.e., alliances with other biotechnology firms). The value is updated yearly and is, thus, cumulative. The data for the variable was derived from the Glostra news-event database.

Eight, we introduce the *financing* variable into the models in order to control for the possibility that biotechnology firms that receive equity financing experience lower failure rates than firms that do not (see e.g., Niosi, 2003). Financing was measured as a dummy variable coded “one” after the year firm received its first private equity placement. As the exact amount of private equity invested in the firms was missing in many cases, we were not able to take this into account in the operationalization. Data for the measure was derived from the SDS Platinum database, containing information of private equity placements made around the globe.

Finally, as the results of earlier research have often shown that biotechnology firms that locate in biotechnology cluster are more successful and experience lower failure rate than firms outside clusters (DeCarolis et al., 1999; Deeds et al., 1997, 1998; Folta, Cooper, & Baik, 2006), we also control for this possibility. *Location in a cluster* is a dummy variable coded as “one” for new biotechnology firms that locate in a geographical cluster (Helsinki, Espoo, Vantaa, Kauniainen, Turku, Tampere, Kuopio, and Oulu) and “zero” otherwise. We derived the yearly updated data for the location of biotechnology firms from the National Board of Patents and Registration of Finland. Tables 1 and 2 present descriptive statistics of all independent and control variables: Table 1 includes the descriptive statistics for the research sample 1 and Table 2 for the sample 2.

Tables 1 and 2 about here

Research Method

The rate of firm failure (μ(t)) is modeled using the instantaneous rate of firm failure. This hazard rate is defined as the limiting probability of a firm failure between *t* and *t* + *Δt*, given that the firm was operating at *t*, calculated over *Δt*:

$$\mu(t) = \frac{\Pr(t, t + \Delta t \mid t)}{\Delta t}.$$

Parametric estimations of the hazard rate require assumptions about the effect of time (in these models, age) on mortality. There is disagreement about the appropriate parametrization of age dependence in organizational mortality, so a stochastic piecewise exponential model, which allows the failure to vary in an unconstrained way over preselected age ranges (Barron, West, & Hannan, 1994; Tuma & Hannan, 1984) will be employed. In the model, the breakpoints for the pieces are denoted as $0 \leq \tau_1 \leq \tau_2 \leq \ldots \leq \tau_p$. With the assumption that $\tau_{p+1} = \infty$, there are P periods: $I_p=\{u \mid \tau_p \leq u \leq \tau_{p+1}\}$, p=1, … , P. The estimated piecewise exponential model is, thus, of the form:

$$\mu(u,t) = \exp(\alpha_1)\exp(\beta X), u \in I_p,$$

where α_1 is a constant coefficient associated with the /th age period, X the vector of covariates, and β the associated vector of coefficients. Based on distribution of events and estimates from exploratory analyses, in the research sample 1, we split the age scale into four pieces, with yearly breakpoints at 2, 5, and 9. As regards the sample 2, we split the age scale into three pieces, with yearly breakpoints at 3 and 7.

Model Specification

The life-histories of each biotechnology firm are broken into one-year spells to incorporate time-varying covariates, yielding 724 spells (416 spells in models with heterogeneity variables included) for Sample 1 and 1259 spells for Sample 2. The analysis period starts from January 1, 1978, the year when the first firms in the samples were established. The end date of the analysis is December 31, 2006. As regards the Sample 1, three models were further tested. Model 1 is a baseline model that incorporates the control variables. Models 2 and 3 then introduce the two variables for the technological heterogeneity. For Sample 2, we test two further models. Model 4 is a baseline model that incorporates all the control variables. Model 5 includes the market niche width variable. The models are estimated by the method of maximum likelihood as implemented with a user-defined routine in STATA 9.0 (Sorensen, 1999). All the covariates are lagged of one year to avoid problems of simultaneity.

RESULTS

Table 3 presents the results of the analysis for Sample 1.

Table 3 about here

Starting from model 2 that includes the variable *H1* for technological niche width, measured as the logarithm of the number of different patent sub-classes in a biotechnology firm's patent portfolio, we notice that the variable has a negative (-0.709) and statistically significant ($p < 0.05$) effect on the rate of firm failure. Thus, the result offers support for hypothesis 1, implying that technological generalism lowers the biotechnology firm's failure rate. Second, model 3 incorporates our other technological heterogeneity variable, *H2*, measured as a function of number of sub-classes on a firm's patent portfolio and the interdependence of sub-classes of the portfolio. A lower value of the measure associates to a wider technological niche for a firm. Also this model offers support for hypothesis 1: the variable has a positive (0.051) and statistically significant effect ($p < 0.05$) on the rate of firm failure.

Finally, we can also assess the results of the analysis in the light of the introduced control variables. First, it seems that at least among the population of these firms, density dependent legitimation and competition seem to play no role: the effects of the density variables are non-significant in all the models, and furthermore, the coefficients of the densities in half of the models imply inverted-U shaped relationship between density and rate of failure, which is against what the theory suggests. Second, we notice that firm size has a negative and statistically significant effect ($p < 0.05$) on failure rate in every model, as predicted by standard ecological theory. Third, also being independent seems to lower biotechnology firms' failure rate ($p < 0.10$). The effects of other variables are generally non-significant (particularly in models 2 and 3).

Turning into the results of the failure analysis for the sample 2, model 5 in Table 4 shows that the variable for the market niche width has a statistically significant ($p < 0.05$) positive effect (1.584) on biotechnology firms' failure rate. Thus, the result offers support for Hypothesis 2, suggesting that generalism (activity in several sub-sectors) in market domain has a negative effect on firm survival.

Table 4 about here

Additionally, in models 4 and 5, many of the effects of the control variables seem to also have statistically significant effects on failure rates. First, we notice that in accordance with the previous models, large size and independent ownership status lower firms' failure rate. Second, number of alliances seems to lower firms' rate of failure according to both of the models. Third, as regards the effects of the density variables, we notice that own sector density raises firms' failure rate (and offer no support for the density-dependence theory). Additionally, the coefficients of the industry level densities have the signs suggested by the density-dependence theory; however, all the effects (except one) are non-significant.

DISCUSSION AND CONCLUSIONS

We set the aim of the present paper onto understanding better how generalist vs. specialist strategy affects firm success/survival in emerging, technology based industries that operate below carrying capacity. A fundamental notion is that firms may adopt generalist/specialist strategies independently in two key dimensions of the underlying environmental niche: markets and technology. It was hypothesized that due to unpredictability and coarse-grainedness, "red queen" competitive races, and other characteristics associated to the technological dimension and related environmental change, firms that hold a broad technological scope (i.e. technological generalists) have better chances of survival in such settings (Hypothesis 1). At the same time, firms holding a narrow market scope (i.e. market specialists) will survive better because of disadvantages from multiple category membership, lack of positional advantages, and relative predictability and fine-grainedness of the market environment (Hypothesis 2). The hypotheses were tested with statistical models on data from the modern biotechnology industry in Finland between 1973-2006.

The results from the empirical tests provide direct support for both hypotheses, and thus offer strong validation for the theoretical arguments. In particular, both of the variables used to measure technological scope or niche width resulted into similar results. In addition, the results should be at least somewhat robust taking into consideration the large variety of control variables, relating to both firm- and industry specific characteristic that may affect survival, that were included in the models. In fact, the effects of many control variables are in line with earlier research (e.g., size, ownership status, and alliances).

Also a quick qualitative examination of a sub-sample of the included biotechnology firms yields results that are in line with the theoretical arguments. First, GeneOS did have a narrow patent portfolio covering only few patent classes, and had only one product in development. The firm eventually disbanded. Similarly, Diabor also had only few patent classes and only one product in development and experienced a disbanding. In contrast, Jurilab has a patent portfolio with a large number of classes, as well as a heterogeneous R&D portfolio. The firm is still in operation. Similarly, Karyon-CTT has a patent portfolio with large number of sub-classes and a heterogeneous technology portfolio, and is still in operation.

The findings of our study yield important contributions to both theory and empirical research. Considering first the theoretical contributions, the paper addresses existing theorizing in both organizational ecology and strategic management. For the ecological domain the paper adds to the existing stocks studies that demonstrate the analytical and explanatory power of concepts such as organizational environment, niche, forms, resources and the evolutionary approach in general. Our results suggest that it is relevant to take a macro perspective to understand how organizations are interrelated via their common environment, and how the strategic scope adopted by firms affects their survival changes in this regard. Earlier research in niche width dynamics has focused strongly to the process of resource partitioning in very mature industries. This earlier focus has been motivated largely because other ecological theories have not been able to explain a common phenomenon of density resurgence in very mature populations. However, questions relating to niche width dynamics in young, emerging fields should be equally interesting. The study at hand seeks to advance this important line of research also towards emerging populations. To add, our study contributes to ecological reasoning by making a clear distinction between the technology and output-market dimensions within organizations' external resource space. A different, more general way to express the same dimensions would be to express them as the input and output dimensions of the resources consumed by organizations. This way, the theoretical ideas presented in this paper might be generalizable to many other organizational contexts than just technology based industries.

As for research in strategic management, the paper again demonstrates the validity of ecological thinking and theorizing in the context of strategic management (cf. Dobrev et al., 2006). In strategic management, the idea of focus vs. broad/diversification strategies is not new (cf. Porter, 1985). However, the present study assists in scrutinizing and further specifying how and why firms adopt either strategy. Because of its strategic management flavor, the ideas and results of our study also mean that they have relevance to management practice – lack of which has sometimes been a target of criticism towards the ecological approach. Here managers can make direct inferences on how to focus their technological and market/offering related activities given specific industrial settings - in maximizing their firms' survival chances.

The paper also yields methodological contributions by continuing and extending a long stream of methodological traditions in both ecological / life-history modeling, as well as the use of patent data to make inferences of firms' characteristics and behavior in the technological domain. In particular, the paper continues to bring forward a specific patent-based heterogeneity measure of technological heterogeneity (Fleming et al., 2001), and supports its validity in ecological research.

We also identify a number of possible limitations regarding the data and methods. First, there are certain problematic issues in using patents and the number of patent classes in measuring the width of technological niche. The mere number of classes doesn't necessarily reflect true heterogeneity, i.e. differences between individual classes are not necessarily linearly additive from the perspective of overall heterogeneity. An attempt to correct this problem was the use logarithmic measures. Moreover, we believe that demonstrating different classes in fact relates fairly well to how many different technological domains a company has to master. Second, one might argue that the number of patents and sub-classes does not correlate with the actual diversity of a firm's R&D portfolio. One firm might have one patent with five individual classes, but forming a platform for five different R&D projects. At the same time, another firm might have 30 patents, 100 sub-classes but only two realistic R&D projects. However, as the above qualitative examination of some of our sample firms shows, the number of patents and patent classes tends to correlate with the overall heterogeneity of the firms' activities in the technological domain.

As for the market based measures, the categorization is a result of extensive but still subjective firm-level coding based on a multitude of company-specific documents and other information. However, we believe the data is very accurate since the categorization was tested and confirmed by using a special card-sorting technique in the interviews of six industry experts. Finally, there is always the question of the generalization of the results beyond Finnish biotechnology, which ultimately needs the efforts of further studies in estimating the same effects on different populations.

As for future research, we propose the following. First, how could the theoretical ideas and empirical measures be transferred into other kinds of industrial contexts? We already noted that it might be possible to extend and generalize the technology and market dimensions to input and output related resources of any organization. Even though lucrative at first glance, this conceptual idea is certainly something that requires further elaboration and examination by ecological researchers. An intriguing question is, would the predictions regarding specialism and generalism within the input and output dimensions be equal to our propositions in the market vs. technology space? Another generalizability issue relates to the empirical measures. If a generalized input/output conceptualization was adopted, how to empirically measure these dimensions? The patent based measures used in the present paper relate strongly to the technological domain.

Second, our study necessitates still further broadening of the niche width/dynamics research stream towards other than mature populations, and setting up research questions such as: What kind of dynamics play role in the interaction and importance of different niche dimensions? Does the importance of market and technological niche domains change in the evolution of the industry? How interrelated are they? Are both domains equally important? What is their combined effect (how the firm should be positioned in order to achieve the best outcome)? What is the effect of other niche dimensions (Podolny et al., 1996)? In sum, several potentially fruitful lines for future research can be identified regarding the dynamics and different dimensions of niches.

Finally, new methodological questions relate to e.g. the usage of patent classes in measuring overlaps in technological niche width and this competitive crowding in this dimension. Similarly, the potential usability of news-event data in identifying firms' market domains should be investigated.

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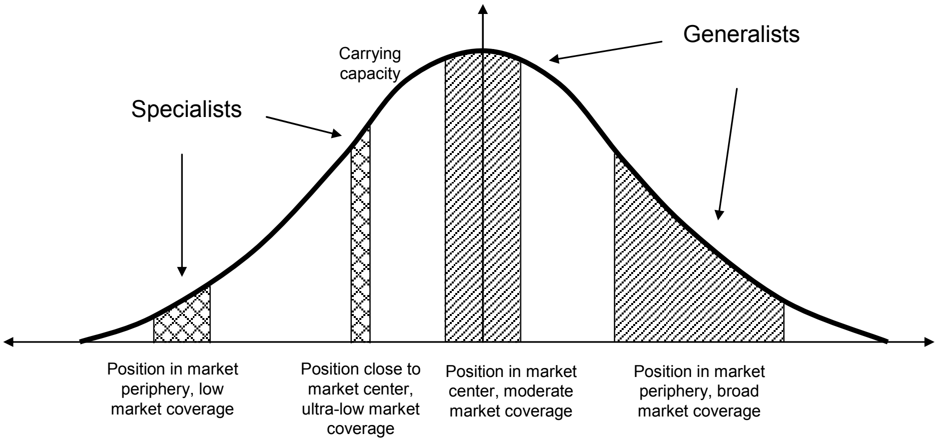

Figure 1: Specialism vs. generalism in the market domain

Market scope
(coverage + position)

Technological scope (stock of routines & knowledge)	Narrow	Wide
Narrow	Specialist	S - G
Wide	G - S	Generalist

Figure 2: Conceptual summary of strategic scope in technology vs. market domain

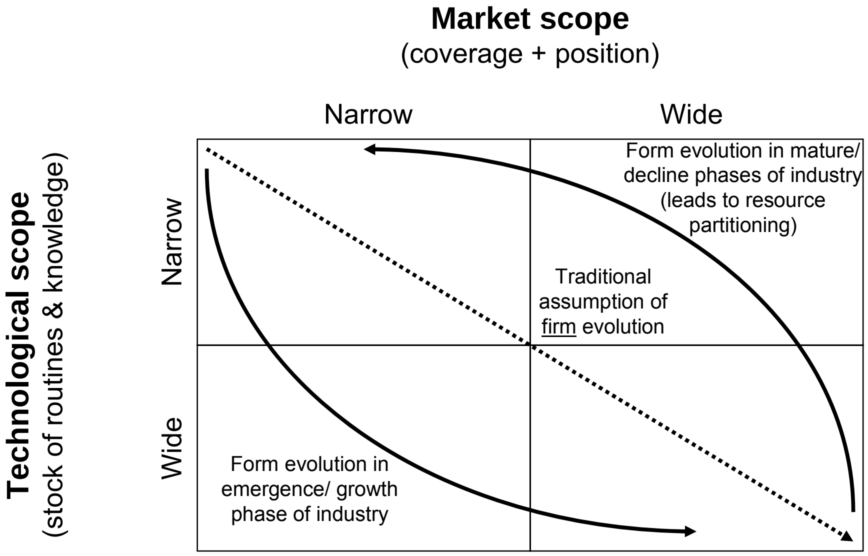

Figure 3: Paths of form evolution

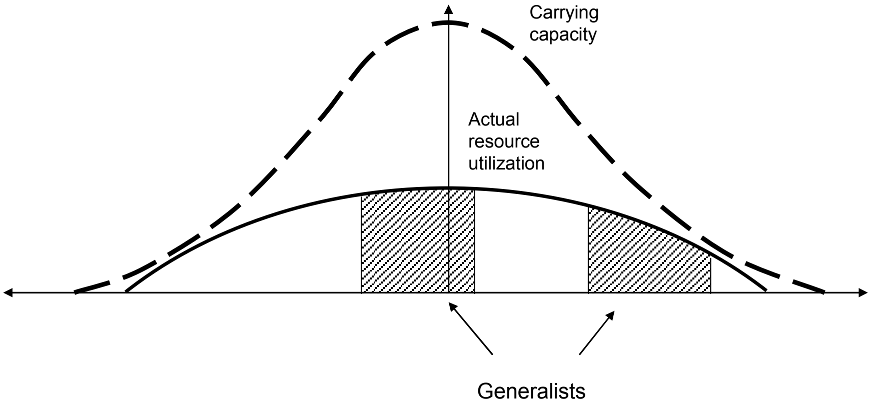

Figure 4: Operation below carrying capacity

Table 1: Basic statistics and correlation matrix for failure analysis for the sample 1.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1. Age	5.357	4.651	1.0000											
2. H1	2.564	1.129	0.2038	1.0000										
3. H2	8.082	15.697	-0.2067	-0.5610	1.0000									
4. Biopharmaceuticals	0.414	0.493	-0.2871	0.1991	0.0254	1.0000								
5. Diagnostics	0.550	0.498	0.1760	-0.3343	0.0851	-0.4436	1.0000							
6. Biomaterials	0.150	0.358	0.0329	0.2447	-0.1511	-0.3215	-0.4477	1.0000						
7. Patents	3.746	7.952	0.4875	0.5925	-0.2508	-0.1524	-0.1094	0.2973	1.0000					
8. Alliances	2.372	3.361	0.5763	0.3453	-0.2168	-0.1116	0.1036	-0.0134	0.4681	1.0000				
9. Ownership status	0.830	0.376	-0.1400	-0.1413	0.0328	-0.1261	0.0534	-0.1218	-0.3524	-0.2130	1.0000			
10. Size	0.527	13.896	0.4209	0.3388	-0.2194	-0.2294	0.2076	-0.0679	0.6096	0.6265	-0.2445	1.0000		
11. Financing	0.276	0.393	0.2618	0.2068	-0.1313	-0.0148	0.0672	0.0892	0.3435	0.4542	-0.2988	0.3543	1.0000	
12. Cluster location	1.754	0.873	-0.2526	0.0367	0.0150	0.0641	-0.0608	0.1008	0.0466	-0.3447	-0.0736	-0.1521	-0.0240	1.0000
13. N_{he}	2.780	46.044	0.3144	0.3316	-0.2356	0.0738	-0.0822	0.0242	0.1252	0.0870	0.1020	0.0662	-0.1125	-0.0359
14. N_{he}^2	5.070	2427.8	0.3161	0.3240	-0.2140	0.0814	-0.0669	0.0272	0.1300	0.0827	0.0849	0.0519	-0.1004	-0.0318
15. N_{all}	1.503	86.008	0.3064	0.3279	-0.2280	0.0751	-0.0804	0.0283	0.1195	0.0818	0.1054	0.0657	-0.1141	-0.0403
16. N_{all}^2	85.361	8463.9	0.3016	0.3186	-0.2043	0.0812	-0.0663	0.0304	0.1208	0.0767	0.0914	0.0546	-0.1031	-0.0391
17. Time	31.765	21.134	0.3254	0.3374	-0.2529	0.0645	-0.0718	0.0198	0.1357	0.0922	0.1015	0.0663	-0.1093	-0.0360

Variable	13	14	15	16	17
13. N_{he}	1.0000				
14. N_{he}^2	0.9811	1.0000			
15. N_{all}	0.9854	0.9693	1.0000		
16. N_{all}^2	0.9591	0.9740	0.9853	1.0000	
17. Time	0.9850	0.9800	0.9585	0.9383	1.0000

Table 2: Basic statistics and correlations for failure analysis for the sample 2.

Variable	**Mean**	**S.D.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1. Age	5.024	4.382	1.0000												
2. Market niche width	1.556	.857	-0.0571	1.0000											
3. R&D -service	.24	.427	-0.1478	0.2059	1.0000										
4. Agrobiotechnology	.078	.268	-0.0715	0.3267	-0.0799	1.0000									
5. Bioenergy	.014	.119	-0.0404	0.2653	-0.0677	0.0649	1.0000								
6. Biomaterials	.045	.208	0.0649	-0.1159	-0.2066	-0.1069	-0.0443	1.0000							
7. Bioproduction	.125	.331	-0.0193	0.5064	0.0230	0.3284	0.3179	-0.1393	1.0000						
8. Devices	.129	.336	0.0883	0.2712	-0.1391	-0.0414	-0.0464	-0.1199	-0.0818	1.0000					
9. Diagnostics	.348	.476	0.1325	0.2785	-0.1291	-0.1188	-0.0880	-0.1708	-0.1206	0.3790	1.0000				
10. Enzymes	.083	.275	0.0324	0.0845	-0.0942	0.0636	-0.0361	-0.1104	0.0344	-0.1157	-0.0556	1.0000			
11. Environment	.055	.228	-0.0636	0.2019	-0.0781	-0.0179	0.5001	-0.0886	0.2037	0.0839	-0.1392	-0.0723	1.0000		
12. Functional food	.126	.332	-0.0422	0.3417	-0.0232	0.1394	0.0348	-0.1398	0.2313	-0.1110	-0.2175	-0.0533	0.0030	1.0000	
13. Biopharmaceuticals	.227	.419	-0.0995	0.1934	-0.0594	-0.0509	-0.0651	-0.0759	-0.1075	-0.2086	-0.1281	-0.1141	-0.1303	0.1029	1.0000
14. Patents	2.932	7.535	0.3823	-0.1188	-0.1824	-0.0887	-0.0371	0.2823	-0.1054	0.0327	-0.0461	-0.0528	-0.0520	-0.1159	0.0666
15. Alliances	1.837	2.841	0.4580	-0.1207	-0.1066	-0.1013	-0.0638	-0.0083	-0.1311	-0.0703	0.0560	0.1249	-0.1176	-0.0363	0.0604
16. Ownership status	.833	.373	-0.0357	-0.0549	0.1366	-0.2438	0.0000	-0.0130	-0.1263	0.0202	0.0495	-0.1057	-0.0140	-0.0416	0.0689
17. Size	11.184	23.778	0.3631	-0.0920	-0.1360	0.0942	-0.0429	-0.0264	-0.1158	0.1180	0.0649	0.0122	-0.0846	-0.1155	-0.0194
18 Financing	.277	.448	0.2363	0.0594	-0.1360	0.0784	-0.0746	0.0680	-0.0203	0.0572	0.0357	0.0591	-0.0556	-0.0485	0.1314
19. Cluster location	.815	.389	-0.1147	0.0543	0.1096	-0.2127	0.0574	0.1753	-0.0232	0.0315	0.0475	-0.1690	-0.1099	-0.0097	0.0867
20. N_{sect}	50.883	34.029	0.0897	0.6715	0.2137	-0.0144	-0.0170	-0.2581	0.0534	0.2916	0.3668	-0.1332	-0.0477	0.2783	0.5139
21. $N_{sect}^2/100$	3.746	4.885	0.0527	0.6577	0.2454	0.0089	-0.0361	-0.1500	0.0180	0.2324	0.3060	-0.1163	-0.0277	0.2608	0.4814
22. N_{all}	217.530	49.41	0.2953	-0.1888	0.1677	-0.1812	-0.2067	0.0341	-0.2743	-0.0548	-0.1166	0.0013	-0.1447	-0.0440	0.1014
23. $N_{all}^2/1000$	49.759	19.16	0.2995	-0.1794	0.1696	-0.1630	-0.1963	0.0308	-0.2658	-0.0537	-0.1151	0.0023	-0.1427	-0.0484	0.0975
24. Time	24.285	5.338	0.3102	-0.1924	0.1711	-0.1905	-0.1970	0.0378	-0.2678	-0.0645	-0.1184	-0.0020	-0.1411	-0.0472	0.0977

Variable	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
14. Patents	1.0000										
15. Alliances	0.4842	1.0000									
16. Ownership status	-0.2544	-0.1149	1.0000								
17. Size	0.5312	0.5305	-0.2768	1.0000							
18 Financing	0.3960	0.4952	-0.0989	0.3844	1.0000						
19. Cluster location	0.0790	-0.0669	0.1818	-0.0159	0.0438	1.0000					
20. N_{sect}	-0.0350	0.0008	0.1190	-0.0208	0.0781	0.0974	1.0000				
21. $N_{sect}^2/100$	-0.0253	-0.0511	0.0966	-0.0278	0.0499	0.0841	0.9485	1.0000			
22. N_{all}	0.1672	0.1358	0.1215	0.0073	0.0114	0.0108	0.2884	0.2636	1.0000		
23. $N_{all}^2/1000$	0.1734	0.1343	0.1084	0.0189	0.0163	0.0202	0.2883	0.2686	0.9930	1.0000	
24. Time	0.1828	0.1479	0.1122	0.0112	0.0228	0.0109	0.2750	0.2498	0.9802	0.9741	1.0000

Table 3: Piecewise exponential models of firm failure for the sample 1.

Variables	Model 1	Model 2	Model 3
Firm age			
0 ≤ u < 2	-10.285*	-7.294	-8.444
	(4.165)	(5.704)	(5.841)
2 ≤ u < 5	-8.172*	-4.707	-7.55
	(4.077)	(5.589)	(5.626)
5 ≤ u < 9	-7.175†	-3.374	-6.035
	(4.08)	(5.671)	(5.668)
u ≥ 9	-8.092*	-5.003	-7.611
	(4.099)	(5.698)	(5.711)
H1		-0.678*	
		(0.337)	
H2			0.052*
			(0.024)
Biopharmaceuticals	-0.128	0.19	-0.085
	(0.700)	(1.027)	(1.004)
Diagnostics	-0.427	-0.766	-0.83
	(0.707)	(1.024)	(1.004)
Biomaterials	-1.399	-0.881	-0.91
	(0.973)	(1.220)	(1.246)
Patents	-0.026	0.066	-0.006
	(0.079)	(0.086)	(0.082)
Alliances	-0.26	-0.252	-0.275
	(0.171)	(0.216)	(0.214)
Ownership status	-1.273*	-1.424†	-1.469†
	(0.537)	(0.753)	(0.758)
Size	-0.075*	-0.09*	-0.09*
	(0.038)	(0.043)	(0.043)
Financing	0.371	0.423	0.619
	(0.565)	(0.668)	(0.688)
Cluster location	0.767	-0.749	-0.77
	(0.792)	(0.216)	(0.84)
N_{he}	-0.489	0.193	0.239
	(0.530)	(0.727)	(0.705)
N_{he}^2	0.003	-0.003	-0.004
	(0.005)	(0.007)	(0.007)
N_{all}	0.249	-0.199	-0.256
	(0.336)	(0.462)	(0.451)
N_{all}^2	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Year	0.443	0.621	0.788
	(0.349)	(0.499)	(0.525)
Log likelihood	-45.4	-23.19	-23.06
Number of failures	29	18	18
Number of subjects	87	67	67
Number of spells	724	416	416

* = $p < 0.05$; † = $p < 0.10$. Standard errors in parentheses.

Table 4: Piecewise exponential models of firm failure for the sample 2.

Variables	Model 4	Model 5
Firm age		
$0 \leq u < 3$	-1.556	-2.306
	(3.202)	(3.347)
$3 \leq u < 7$	-0.33	-1.062
	(3.279)	(3.417)
$u \geq 7$	0.057	-0.579
	(3.295)	(3.429)
Market niche width		1.584*
		(0.747)
Service	-1.552*	-3.148*
	(0.744)	(1.078)
Agrobiotechnology	0.741	-0.711
	(0.549)	(0.843)
Bioenergy	-1.121	-2.721*
	(1.000)	(1.255)
Biomaterials	-1.484†	-2.977*
	(0.807)	(1.06)
Bioproduction	-0.149	-1.728†
	(0.534)	(0.916)
Devices	-1.518†	-2.978*
	(0.884)	(1.115)
Diagnostics	-1.293†	-2.754*
	(0.758)	(0.993)
Enzymes	-0.414	-1.950*
	(0.658)	(0.976)
Environment	1.011†	0.439
	(0.59)	(0.884)
Functional food	-0.927	-2.308*
	(0.692)	(0.923)
Biopharmaceuticals	-1.804†	-3.309*
	(1.046)	(1.267)
Patents	0.036	0.044
	(0.049)	(0.048)
Alliances	-0.253†	-0.27†
	(0.139)	(0.142)
Ownership status	-0.81*	-0.823*
	(0.414)	(0.414)
Size	-0.064*	-0.065*
	(0.031)	(0.032)
Financing	0.282	0.243
	(0.440)	(0.442)
Cluster location	0.521	0.534
	(0.432)	(0.440)
N_{sect}	0.059*	0.06*
	(0.029)	(0.029)
$N_{sect}^2/100$	-0.092	-0.123
	(0.105)	(0.102)
N_{all}	-0.061†	-0.054
	(0.034)	(0.034)
$N_{all}^2/1000$	0.081	0.069
	(0.078)	(0.08)
Year	0.243*	0.232†
	(0.123)	(0.125)
Log likelihood	-81.51	-83.32
Number of failures	53	53
Number of subjects	163	163
Number of spells	1259	1259

* = $p < 0.05$; † = $p < 0.10$. Standard errors in parentheses.